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New Feature for Shadow Detection by Combination of Two Features Robust to Illumination Changes

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Abstract

Computer vision methods need to deal with shadows explicitly because shadows often have a negative effect on the results computed. A new shadow detection method is proposed. The proposed method is a shadow model based method. A new feature for detecting shadows is introduced. The feature is obtained by L*a*b* components, Peripheral Increment Sign Correlation and Normalized Vector Distance. These features are robust to illumination changes. Shadows can be treated as local illumination changes. Using these features results in removing shadow effects, in part. The histogram is generated by the three features and is treated as the feature for detecting shadows. The SVM is used for the classifier. The SVM is trained in advance by shadow data and the trained SVM is used for detecting shadows. The proposed method can extract shadows with the accuracy similar to the previous approach in shorter time. Results are demonstrated by experiments using the real videos.

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Keywords: Shadow Detection; Shadow Model; Local Binary Pattern; Nomaized Vector Distance; Support Vector Machine

1. Introduction

Many methods for detecting moving objects have been proposed in the field of computer vision. They are often used at a preprocessing step of other methods. One of the problems of the object detection is that shadows are detected as moving objects. Accordingly, shadows have a negative effect on the accuracy of the result. As shown in Fig. 1, there is a case where multiple objects are extracted as one object because of the effect of shadows. Another case is that accuracy of tracking is decreased when information obtained as the information of the target object includes cast shadow of the target object. Shadows should be detected and removed. Many methods to detect shadows and to remove them have been proposed.

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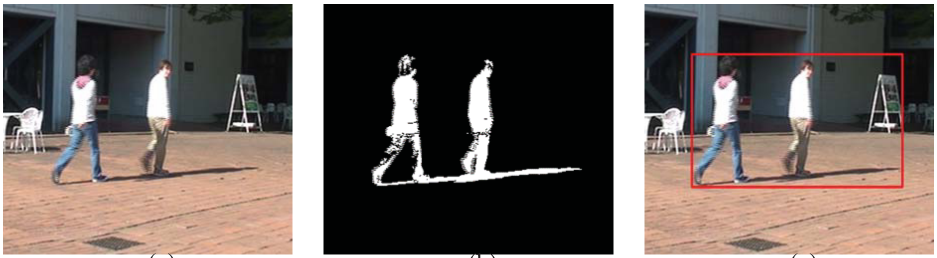


(a) (b) (c)

Fig. 1. Example of Negative Effect of Shadow: (a) Original Image, (b) Result of Object Detection , and (c) Result of Detected Object Region. In this case, two persons need to be detected, but only one region is detected because of the effect of the shadow.

Some methods use multiple cameras[1,2] for shadow detection. These methods can detect shadows accurately but cannot be applied to images obtained from a single camera. Methods using a single camera have wider application than those using multiple cameras. Images taken by a single fixed camera are handled in this paper.

Methods using another color space, such as YUV, HSV and L*a*b*, to detect shadows have been proposed[3,4,5]. These methods use the characteristic that color tones in shadow regions change little in comparison with original tones. But those are not the same. Stability with respect to imaging conditions remains a problem.

According to the paper[6], most of the methods of shadow detection take a shadow model into account. Recently, methods which model shadows as a mixture of distributions were proposed[7,8,9,10]. It is difficult, in general, to determine the proper number of distributions to use. To address these issues, a shadow model constructed by a nonparametric Bayesian scheme was proposed[9]. The method[10] improves the accuracy of the detected result by using three features which are robust to illumination changes. Speeding up remained as future work.

This paper proposes a new method for extracting cast shadows of moving objects. A new feature for shadow detection is introduced. The feature is generated by the Normalized Vector Distance (NVD)[11] and the Peripheral Increment Sign Correlation (PISC)[12]. Both features are robust to illumination changes. The features remove shadow effects in part and can detect shadows. After segmenting the image by color, the histogram is constructed by PISC and NVD at each region. The histogram is treated as the shadow feature. The Support Vector Machine (SVM) with the histogram intersection kernel is used for the classifier. The proposed method can process faster than the previous method[10]. Results are demonstrated by the experiments using the real videos.

The paper continues as follows: NVD and PISC are described in the section 2. In the section 3, the proposed feature for shadow detection is explained in detail. In the section 4, the shadow detection method is described. After that, the experimental results are shown in the section 5. In the last section, we conclude the paper.

2. Features Robust to Illumination Changes

In this section, NVD and PISC, which the proposed method uses for obtaining the feature, are described.

2.1. Normalized Vector Distance

NVD is a distance between the normalized irradiances of the background image and that of the observed image. After dividing an image into small blocks, the image irradiances are normalized at each block and NVD is calculated by the normalized irradiances. In this paper, NVD at a pixel, $\boldsymbol{x} = (x, y)$, is calculated by the following equations.

$$NVD_{x,y} = \left| \frac{I_{x,y}}{|\mathbf{I}_{x,y}|} - \frac{B_{x,y}}{|\mathbf{B}_{x,y}|} \right| \tag{1}$$

$$|\mathbf{I}_{x,y}| = \sqrt{\sum_{i=-N_b/2}^{N_b/2} \sum_{j=-N_b/2}^{N_b/2} |I_{x-i,y-j}|^2} \tag{2}$$

$$|\mathbf{B}_{x,y}| = \sqrt{\sum_{i=-N_b/2}^{N_b/2} \sum_{j=-N_b/2}^{N_b/2} |B_{x-i,y-j}|^2} \tag{3}$$

where $NVD_{x,y}$ means the NVD value at $\boldsymbol{x}$, and $I_{x,y}$ and $B_{x,y}$ mean the data at $\boldsymbol{x}$ in the observed image and the background image, respectively. N_b represents the block size.

The direction of the vector which consists of the data in the small block does not change much by the effect of illumination changes[11]. NVD is a feature robust to illumination changes. Shadows can be regarded as local illumination changes. NVD can remove the effect of shadows, in part.

2.2. Peripheral Increment Sign Correlation

PISC is a correlation of the Local Binary Pattern (LBP)[13] of a background image and that of an observed image. PISC is obtained by Eq. (4).

$$PISC(\boldsymbol{x}) = \frac{1}{N} \sum_{k=1}^{N} (f_k(\boldsymbol{x}) \cdot b_k(\boldsymbol{x}) + (1 - f_k(\boldsymbol{x})) \cdot (1 - b_k(\boldsymbol{x}))) \tag{4}$$

where $PISC(\boldsymbol{x})$ means the PISC value at $\boldsymbol{x}$, $f_k(\boldsymbol{x})$ and $b_k(\boldsymbol{x})$ represents the sign of the difference of the pixel value between $\boldsymbol{x}$ and its k-th neighbor pixel for the observed image and that for the background image, respectively, and N means the number of the neighbors. $f_k(\boldsymbol{x})$ is set to 0 when the sign is minus. Otherwise, it is set to 1. $b_k(\boldsymbol{x})$ is also set as the same manner. The sign of the difference does not change in the background region by illumination changes and $PISC(\boldsymbol{x})$ does not change much by illumination changes. PISC is also a robust feature to illumination changes and can remove shadow effects, in part.

3. New Feature for Shadow Detection

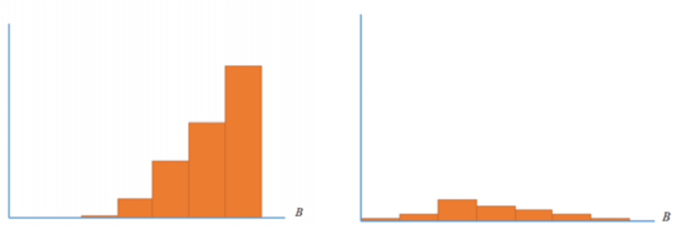
The feature proposed in this paper is explained in detail in this section. The feature is the histogram which is generated by the CIE L*a*b* values, PISC and NVD. The procedure of obtaining the feature is shown in the following.

Step 1. Translating the color space of pixel values from the RGB color space into the L*a*b* color space
Step 2. Calculating PISC
Step 3. Calculating NVD
Step 4. Applying color segmentation
Step 5. Generating Histogram

Each step is explained in detail in the following.

At Step 1, the color space of pixels is translated from the RGB color space into the L*a*b* color space. The pixel values of frames obtained by a camera are usually represented by the RGB color space, but it is not suitable for the shadow detection. When a pixel belonging to a background region at $t-1$ frame becomes the pixel belonging to a shadow region at t frame, RGB values of the pixel become small. The RGB values also become small when a darker object than the background comes at the pixel. The cause of the change of the pixel values cannot be judged from the change of the pixel values themselves. Many methods for shadow detection use the chromaticity information, such as HS components of HSV color space, a*b* components of L*a*b* color space, UV components of YUV color space. The chromaticity changes a little by shadow effects, in general. According to the paper[14], CIE L*a*b* is the most suitable color space for the shadow detection. The proposed method uses the CIE L*a*b* color space.

After translating the pixel values from the RGB color space into the L*a*b* color space, PISC and NVD are calculated at each pixel. Next, the frame is segmented by color. The mean-shift algorithm[16] is used for the segmentation. It can segment the frame while it can apply the smoothing to the frame with keeping edge. After that, the histograms of three components are generated at each segmented region by PISC and NVD. The PISC is divided into the bins of the histogram. After subtracting the NVD value from 1, it is added to the bin according to the PISC value. Both of the PISC value and the value subtracting the NVD value from 1 become smaller when the pixel belongs to the



Histogram for Shadow Region Histogram for Object Region

Fig. 2. Histogram Generated by PISC and NVD

Campus Hallway Highway Lab Room

Fig. 3. Examples of Input Images

shadow region. In contrast, they become larger when the pixel belongs to the object region. As illustrated in Fig. 2, the histogram becomes the graph rising to the right when the region belongs to the shadow region while it becomes the low and flat graph when the region belongs to the object region. The joint histogram of the three histograms is used as the feature for shadow detection.

4. Shadow Detection by Proposed Feature

The proposed method detects shadows by the support vector machine (SVM) which has already trained by the proposed feature. The SVM can handle a non-linear classification by the kernel trick, which maps the data into the high-dimensional space. It is robust to noises because of the margin maximization. These are the reasons the proposed method uses the SVM for the classifier. The histogram intersection kernel is used as the kernel function [15] because the feature used by the proposed method is the histogram.

In the training step, object regions which include shadow regions are extracted by an object detection method, such as the background subtraction. The extracted regions are segmented by the mean-shift segmentation. Next, the proposed feature is obtained at each segmented region. The correct label is given to each region and the SVM is trained using the features and the labels.

In the shadow detection step, object regions are extracted and are segmented. The feature is extracted at each region and it is judged whether each segmented region is the shadow region or not by the SVM trained in advance. The proposed method can process faster than the previous approach because the SVM can process fast.

5. Experiments

Experiments using real videos were done for the evaluation of the proposed method. Five scenes (called Campus, Hallway, Highway, Lab and Room) were used in the experiments. They were introduced by Prati *et al.* [6] and Sanin *et al.* [23], and often used for the evaluation of a shadow detection method. The example image of each scene is shown in Fig. 3.

In the experiments, N_b in Eq. (2) and Eq. (3) is set to 5 and N in Eq. (4) is set to 16.

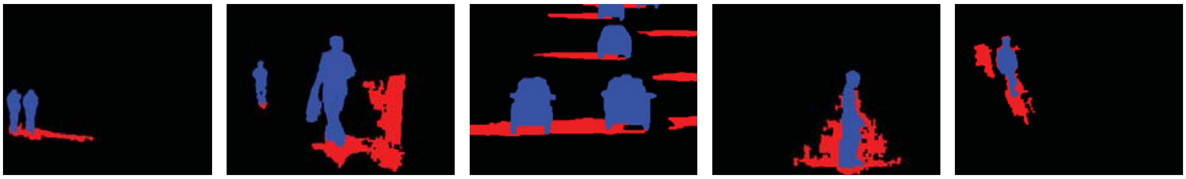


Fig. 4. Ground Truths

For the evaluation, the previous approaches [18,19,20,21,22,10] were also applied to the scenes. The methods [18,19,20,21,22] were evaluated quantitatively in the paper [23]. We used the source codes of the methods which are used in the paper [23] and can be downloaded from the website [24]. The parameters of the methods were decided empirically and no parameter was tuned through the experiments.

The methods were applied to the areas obtained from the ground truths. The areas include foreground objects and those cast shadows. The ground truths of the frames are shown in Fig. 4. Red pixels in the figure denote object pixels and white ones denote shadow pixels.

The results of shadow detection of all methods are shown in Fig. 5. The figures show that the proposed method can obtain more accurate results than the methods [18,19,20,21]. The results of the methods [22,10] and the proposed method except for the Highway scene can be obtained with similar accuracy. The camera moves subtly through the scene. The result of Highway of the proposed method is worse than that of the method [22] because the proposed method assumes the fixed camera.

Next, the results were evaluated quantitatively. The shadow detection rate and the shadow discrimination rate which were introduced in the paper [6] were used. They are calculated by Eq. (5) and Eq. (6), respectively.

$$\eta = \frac{TP_s}{TP_s + FN_s} \tag{5}$$

$$\xi = \frac{\overline{TP_f}}{TP_f + FN_f} \tag{6}$$

where η and ξ mean the shadow detection rate and the shadow discrimination rate, respectively, TP is the number of true positives, FN is the number of false negatives, subscript s denotes shadow, subscript f denotes foreground and $\overline{TP_f}$ is the difference between the correct number of points on foreground objects and the number of points on foreground objects misclassified as shadows.

Table 1 shows η and ξ of all scenes. The values of each scene are the averages of some frames. The numbers of the frames are shown in Table 2. η becomes larger when the pixels which are judged as the shadow pixels exist more even though many misclassified pixels exist in the object regions. Similarly, ξ becomes larger when more object pixels exist even though many misclassified pixels exist in the shadow regions. The overall result is good when both values are high. The averages of η and ξ are also shown in Table 1. The best value of the average of each column is shown by the boldface. The proposed method obtains better results than the methods [19,18,20,21]. On the whole, the method [10] is the most accurate method in the seven methods. However, as shown in Table 1, the accuracy of the proposed method is similar to that of the method [10]. The proposed method judges whether each region is a shadow region or not. When a misjudgment occurs by the proposed method, it has a big influence on the accuracy. There are some cases that some segmented regions include pixels of the moving objects and the background and that some regions have a little information because the regions are too small. On the other hand, the method [10] improves the result after obtaining the shadows by the shadow model. The accuracy of the proposed method may be improved by introducing the method for improving the result.

The processing times of the methods were measured at each scene. The numbers of frames per second are shown in Table 3. The proposed method can process faster than the methods [22,10]. It is shown that the proposed method can extract shadow regions with the accuracy similar to the previous method [10] in shorter time. This is because the processing costs of calculating PISC and LBP are lower than the features used by the method [10] and the SVM can process fast.

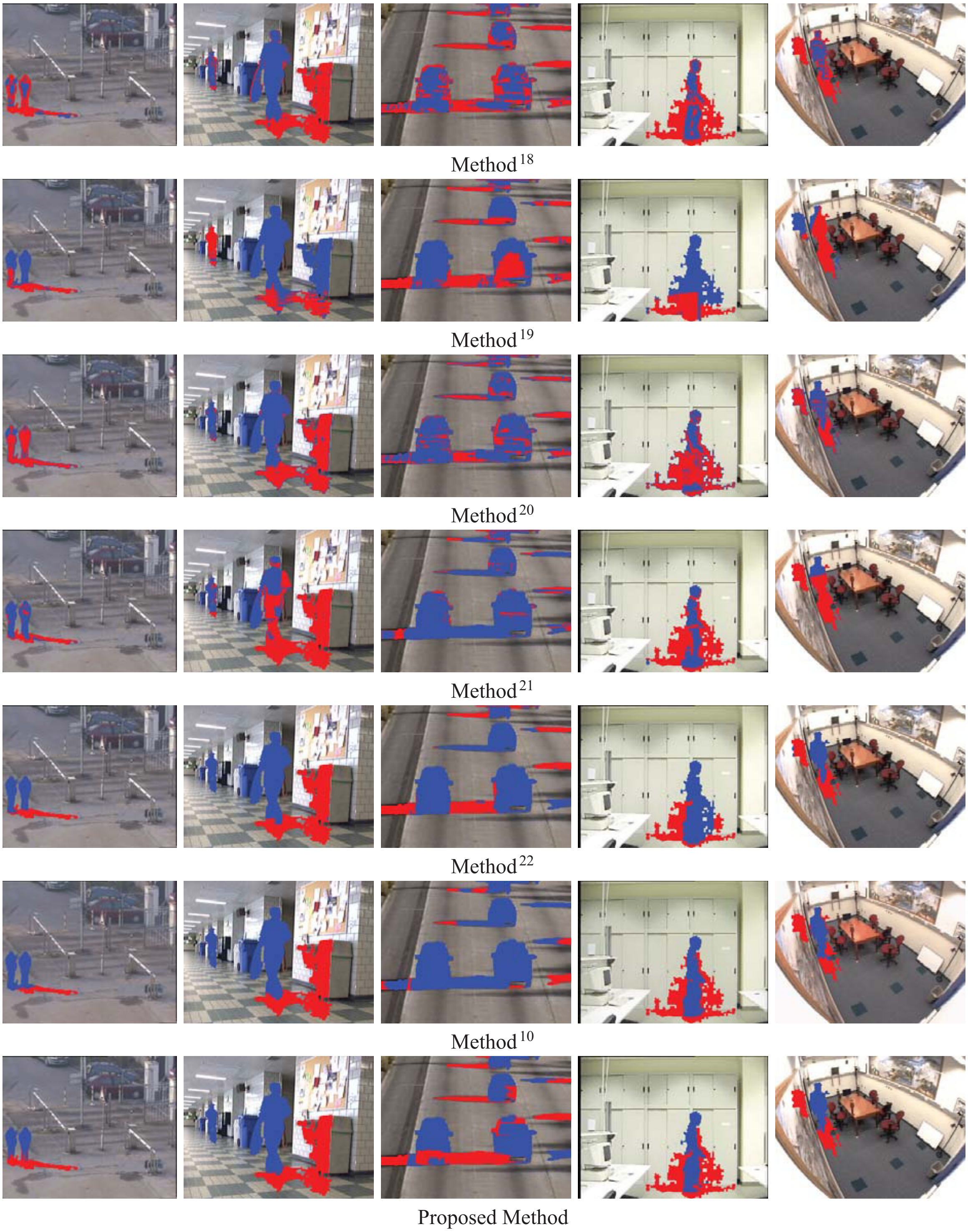


Fig. 5. Results

Table 1. Shadow Detection Rates and Shadow discrimination rates

		Campus	Hallway	Highway	Lab	Room
Method [18]	η	57.53	93.77	76.44	96.61	96.11
	ξ	55.90	79.95	67.26	76.07	66.12
	Average	56.72	86.86	71.85	86.34	81.12
Method [19]	η	66.97	48.70	66.61	47.76	54.96
	ξ	54.35	75.57	74.98	69.20	69.61
	Average	60.66	62.14	70.80	58.48	62.29
Method [20]	η	80.13	82.62	51.00	82.12	80.72
	ξ	47.81	85.89	80.02	81.45	86.77
	Average	63.97	84.26	65.60	81.79	83.75
Method [21]	η	55.59	96.11	17.03	85.31	93.86
	ξ	85.12	65.53	94.00	88.27	62.85
	Average	70.36	80.72	55.52	86.79	78.36
Method [22]	η	51.31	95.19	64.35	60.31	82.73
	ξ	89.74	95.79	95.28	97.52	94.32
	Average	70.53	95.49	**79.82**	78.92	88.53
Method [10]	η	53.25	93.03	30.71	81.68	85.83
	ξ	99.41	98.82	99.95	91.97	95.65
	Average	76.33	**95.93**	65.33	**86.83**	**90.74**
Proposed Method	η	78.82	95.29	63.34	74.78	87.73
	ξ	85.35	94.68	76.73	89.74	88.74
	Average	**82.09**	94.99	70.04	82.26	88.24

Table 2. Numbers of Frames Used for Calculation of Values Shown in Table 1

	Campus	Hallway	Highway	Lab	Room
Number of Frames	41	13	8	14	22

Table 3. Processing Speeds (fps)

	Method [18]	Method [19]	Method [20]	Method [21]	Method [22]	Method [10]	Proposed Method
Campus	52.47	36.31	2.78	2.81	3.45	6.44	17.19
Hallway	20.42	15.87	3.37	1.33	5.01	3.75	14.33
HighwayI	12.57	7.45	3.07	0.77	1.24	6.80	13.05
Lab	21.60	12.52	3.35	1.10	3.94	2.02	14.46
Room	47.75	37.40	3.64	2.58	5.67	3.32	19.84

6. Conclusion

This paper proposed a new feature for the shadow detection. The method used PISC and NVD which are the features robust to illumination changes. The histogram by the features is generated and used for detecting shadows. The SVM with the histogram intersection kernel is used for the classifier.

The processing costs of calculating the PISC and the NVD are low and the SVM can process fast. The proposed method can process faster than the previous approach.

In the experiments, the proposed method can process faster than the previous approach. The accuracy of the proposed method is similar to that of the previous approach. The effectiveness of the proposed method is shown in the experiments.

A Shadow detection method needs to be as fast as it can because it is usually used for a preprocessing of a method, such as an object tracking. The processing time of the segmentation is about 80% of the whole processing time. A faster segmentation method is needed. Further, the accuracy should be improved. These remain as the future works.

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